Journal of Engineering Science and Technology Review 10 (5) (2017) 159 - 173

Research Article

JOURNAL OF
Engineering Science and Technology Review

www.jestr.org

Recent Trends of the Most Used Metaheuristic Techniques for Distribution Network Reconfiguration

Michell Quintero-Duran[1,*], John E. Candelo[1] and Vladimir Sousa[2]

[1]*Department of Electrical Energy and Automation, GITA, Universidad Nacional de Colombia, Carrera 80 No. 65-223, Medellin, Colombia.*
[2]*Department of Energy, GIOPEN, Universidad de la Costa, Calle 58 No. 55-66, Barranquilla, Colombia.*

Received 9 August 2017; Accepted 11 November 2017

Abstract

Distribution network reconfiguration (DNR) continues to be a good option to reduce technical losses in a distribution power grid. However, this non-linear combinatorial problem is not easy to assess by exact methods when solving for large distribution networks, which requires large computational times. For solving this type of problem, some researchers prefer to use metaheuristic techniques due to convergence speed, near-optimal solutions, and simple programming. Some literature reviews specialize in topics concerning the optimization of power network reconfiguration and try to cover most techniques. Nevertheless, this does not allow detailing properly the use of each technique, which is important to identify the trend. The contributions of this paper are three-fold. First, it presents the objective functions and constraints used in DNR with the most used metaheuristics. Second, it reviews the most important techniques such as particle swarm optimization (PSO), genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO), immune algorithms (IA), and tabu search (TS). Finally, this paper presents the trend of each technique from 2011 to 2016. This paper will be useful for researchers interested in knowing the advances of recent approaches in these metaheuristics applied to DNR in order to continue developing new best algorithms and improving solutions for the topic.

*Keywords :*Combinatorial problems; distribution networks; metaheuristics; optimization; reconfiguration

1 Introduction

Power distribution networks are affected by high power losses due to voltage reduction, which allows high currents compared with those in transmission systems. This occurs because the material resistivity of conductors is opposed to the current flow, thereby dissipating energy as heat (i.e., power losses). Distribution system operators (DSOs) have several alternatives for solving this problem. Some of the best options include the use of DG [1–7], capacitor placement [7,8], feeder restructuring [8], and network reconfiguration [9,10]. Reconfiguration is a good option because the network can be optimized with the existing switches or by investing money to optimize the network topology and thereby reduce power losses [11].

DNR involves a change of network topology through tie and sectionalizing switches, which are referred to as "normally opened" and "normally closed," respectively. This is a combinatorial non-linear problem, constrained by the electrical properties of power system elements. The aim of this process is to reduce power losses by identifying the best switch combination in a reasonable timeframe. However, exact algorithms require a lot of time to find a solution, whereas metaheuristics can evaluate different combinations with faster convergence.

Metaheuristic techniques are inspired in both nature and evolutionary processes, emulating particle behavior and the process of evolution through simple mathematical models. The main difference between metaheuristics and conventional methods is the stochastic approach. Many researchers are constantly facing new challenges with stochastic techniques. Some reviews on both reconfiguration and metaheuristics can be found in the scientific literature [12–15]. Nonetheless, we could not find a proper survey about the most relevant metaheuristic techniques directly applied to DNR in recent years.

Therefore, the aim of this paper is to present recent works that use PSO, GA, SA, ACO, IA, and TS. The most used objective functions and constraints for the DNR problem are presented. The search was done based on Scopus and the ISI Web of Science databases for articles in journals and conferences. In addition, the timeframe was defined as between 2011 and 2016 for articles in databases.

The remainder of this paper is set out as follows. Section 2 shows the objective functions and constraints used with the metaheuristic algorithms. Section 3 presents descriptions of the most used metaheuristic techniques and how these have been applied for DNR, and shows some statistics on the topic. Section 4 includes a discussion of the results and, finally, Section 5 presents the conclusions.

2 Reconfiguration objectives and constraints

This section presents the objectives and constraints used with metaheuristic algorithms for the DNR problem. Table 1 summarizes a review of the objective functions and constraints found in the literature for papers presenting PSO, GA, SA, ACO, IA, and TS. It can be seen that the most used objective functions with these metaheuristics are power losses reduction followed by voltage profile improvement and load profile index improvement. Furthermore, the most

*E-mail address: mjquinterod@unal.edu.co
ISSN: 1791-2377
doi:10.25103/jestr.105.20

used equations are (1)–(5). Moreover, the most used constraints are power balance, voltage thresholds, branch current thresholds, feeding of all loads, and number of branches. These constraints are numbered as C1–C5 or equations (20)–(24) in Table 1. Constraints C4 and C5 maintain the radiality of distribution networks.

Table 1 Objective Functions and Constraints

<table>
<tr><th>Objective Function (OF)</th><th>Constraints (C)</th><th>References (R)</th></tr>
<tr><td rowspan="3">OF1. Power losses reduction. Equation (1)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[9,16–90]</td></tr>
<tr><td>C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)</td><td>[91–94]</td></tr>
<tr><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)</td><td>[95–97]</td></tr>
<tr><td>OF2. Voltage profile improvement. Equation (2)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[17,19,28,30–32,36–38,61,62,65,66,89,98]</td></tr>
<tr><td>OF3. Load profile index improvement. Equations (3)–(5)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[9], [17], [19], [33], [61], [65], [73], [90], [99]</td></tr>
<tr><td>OF4. Optimal PMU placement. Equation (6)</td><td>C4 - Feeding of all loads (23)</td><td>[92]</td></tr>
<tr><td>OF5. Total cost of capacitor installation and energy losses reduction. Equation (7)</td><td>C5 - Number of branches (24)
C6 - Minimum PMU's installed (25)
C7 - Maximum allowable daily moving step of LTC's (26)</td><td>[100]</td></tr>
<tr><td>OF6. Voltage sags index reduction. Equations (8)–(9)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)</td><td>[101], [102]</td></tr>
<tr><td>OF7. Priority loads maximization. Equation (10)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[103], [104], [105]</td></tr>
<tr><td>OF8. Power losses reduction in ship´s power systems. Equation (11)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[103], [104]</td></tr>
<tr><td>OF9. Tap changes in transformers reduction. Equation (12)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)
C7 - Maximum allowable daily moving step of LTC's (26)
C8 - Limits for movements of LTC's taps (27)</td><td>[53], [99]</td></tr>
<tr><td>OF10. Capacitor switch operations reduction. Equation (13)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)
C9 - Number of daily switching operations for capacitor banks (28)</td><td>[53]</td></tr>
<tr><td>OF11. Multiobjective energy losses, grid upgrade, transmission power, and reliability cost reduction. Equations (14)–(18)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[106]</td></tr>
<tr><td>OF11A. Energy losses minimization. Equation (15)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[65], [83], [99], [107], [108]</td></tr>
<tr><td>OF12. Switching operations minimization. Equation (19)</td><td>C1 - Power balance (20)
C2 - Voltage node thresholds (21)
C3 - Branch current threshold (22)
C4 - Feeding of all loads (23)
C5 - Number of branches (24)</td><td>[59], [90], [107]</td></tr>
</table>

2.1 Objective functions (OF)
Several equations have been used for DNR. Next, each of the equations used with the metaheuristic algorithms presented in Table 1 is described according to its use in the literature. Here, the term OF1 means Objective Function 1, OF2 means Objective Function 2, and so on, representing the terms defined in Table 1.

2.1.1 Power losses (OF1)
The equation for minimization of technical power losses is (1), where *nbr* is the total number of branches, R_l is the resistance of the branch *l*, and I_l is the current in branch *l*:

$$\text{Min } P_{loss} = \sum_{l=1}^{nbr} R_l I_l^2 \ . \quad (1)$$

2.1.2 Voltage profile (OF2)
The equation for voltage profile improvement is (2), where ΔV_D represents the voltage variation, V_1 the voltage level of the system (voltage base), and V_i the voltage in node *i*:

$$\text{Min } \Delta V_D = \text{Max}\left(\frac{V_1 - V_i}{V_1}\right) \forall i = 1,2...,N \ . \quad (2)$$

2.1.3 Load profile index improvement (OF3)
The equations for load profile index are in (3)–(5), where *LUI* is referred to as line usage index, S_i the apparent power flowing in branch *i*, S_i^{max} is the apparent power threshold for branch *i*, S_{nbr} is the apparent power in branch *n*, S_{nbr}^{max} is the apparent power threshold for the branch *n*, *X* is the *LUI* vector, and *LBI* is the load-balancing index:

$$LUI = \frac{S_i}{S_i^{\max}} \ , \quad (3)$$

$$X = \left[\frac{S_i}{S_i^{\max}} \cdots \frac{S_{nbr}}{S_{nbr}^{\max}}\right] , \quad (4)$$

$$\text{Min } LBI = \text{Var}(X) \ . \quad (5)$$

2.1.4 Optimal PMU placement (OF4)
The equation for optimal placement of phasor measurement units (PMUs) is presented in (6), where ω_i is the cost of PMU installation at bus *i* and x_i is a binary decision variable considering 1 if a PMU is installed at node *i* and 0 otherwise:

$$\text{Min } \sum_{i=1}^{n} (\omega_i x_i) \ . \quad (6)$$

2.1.5 Total cost of capacitor placement and energy losses reduction (OF5)
The equation for reducing the total cost of capacitor placement and energy losses is described in (7), where K_p is the cost of energy, E_{loss} the daily energy losses, K_i the installation cost of capacitor, K_b the purchase cost of capacitor, *y* the number of years to be evaluated, *n* the *n*th capacitor, and *N* the total number of capacitors installed:

$$\min\left[y \times 365 \times K_p \times E_{loss} + \sum_{n=1}^{N} \left({}^{K_i + K_b}\!/_{10} \right) \right] . \quad (7)$$

2.1.6 Voltage sags index reduction (OF6)
Equations (8) and (9) present the reduction of the sags index $SARFI_x$, which represents the average number of root mean square (rms) variation measurement events that occurred over the assessment period per customer served where the specified disturbances are those with a magnitude less than *x* for sags or a magnitude greater than *x* for swells, where *x* is the rms voltage threshold, N_i is the number of customers experiencing the disturbances, N_T is the total number of customers served from the section of the system to be assessed, f_{esti} is the voltage sags number at bus *i*, and f_{refi} is the voltage sags reference value at bus *i*:

$$SARFI_x = \frac{\sum N_i}{\sum N_T} \ , \quad (8)$$

$$\text{Min}(f_{est-i} - f_{ref-i}) \forall i \ . \quad (9)$$

2.1.7 Priority loads maximization (OF7)
Equation (10) maximizes main loads to be served in a ship's power system, where *N* is the total number of loads and p_i is the priority weighting factor associated with a load L_i at bus *i*:

$$\text{Max } \sum_{i=1}^{N} (p_i L_i) \ . \quad (10)$$

2.1.8 Power losses reduction in a ship´s power system reduction (OF8)
The equation for reducing the power losses in ship´s systems is (11), where P_{GEN} and P_{LOAD} represent active power generated and active power consumed by loads, respectively.

$$\text{Min}(P_{GEN} - P_{LOAD}) \ . \quad (11)$$

2.1.9 Tap changes in transformer reduction (OF9)
Equation (12) minimizes the total number of tap changes in a load transformer changer (LTC) element, where A_T is the total operation number of all LTCs in the system, N_P the total number of transformers, N_T is the number of time segments, N_L is the number of load curve segments, $A_{T\cdot n}$ is the total operation number of LTC *n* on the concerned day, $S_{n\cdot t}$ is the position of the *n*th LTC corresponding to time segment *t*, and $S_{n\cdot(t-1)}$ corresponds to the last curve segment of the previous day:

$$\min A_T = \sum_{n=1}^{N_P} A_{T\cdot n} = \sum_{n=1}^{N_T} \sum_{t=1}^{N_L} \left| S_{n\cdot t} - S_{n\cdot(t-1)} \right| \ . \quad (12)$$

2.1.10 Capacitor switch operations reduction (OF10)
In (13), the capacitor switch operations are diminished. Here, A_C is the total operation number of all capacitor bank switches, N_C is the total capacitor banks, and $C_{m\cdot t}$ is the status of capacitor bank switch *m* corresponding to load curve segment *t*. When a capacitor bank is on, $C_{m\cdot t}$ is 1 and 0

otherwise. $C_{m\cdot(t-1)}$ corresponds to the previous day's state of the capacitor bank *m*:

$$\min A_C = \sum_{m=1}^{N_C} A_{C\cdot m} = \sum_{n=1}^{N_C}\sum_{t=1}^{N_L}\left|C_{m\cdot t} - C_{m\cdot(t-1)}\right| . \tag{13}$$

2.1.11 Multiobjective energy losses, grid update, transmission power, and reliability cost reduction (OF11)

Equation (14) is based on the network upgrading cost in year, which is represented as $C^{upg}(y)$, where *y* is the planning years, n_{cl} is the network candidate lines, $UC(x_{ncl}(y))$ is the installation cost of various types of candidate lines (CT) per kilometer, L^{ncl} is the length of line n_{cl}, C^f_{ncl} is the fixed cost of feeder n_{cl}, and $z_{ncl}(y)$ is a binary decision variable that is equal to 1 if feeder n_{cl} is reinforced in year *y* and 0 otherwise:

$$C^{upg}(y) = \sum_{n_{cl}}\left\{UC\left(x_{n_{cl}}(y)\right)\times L^{n_{cl}} + C^f_{n_{cl}}\times z_{n_{cl}}(y)\right\} . \tag{14}$$

Equation (15) (OF11A) represents the total cost of energy losses in year *y*, which is $C^{Loss}(y)$, where *T* is the time periods and *nf* represents the network feeders. The variable $z_{nf}(T,y)$ is binary-based and is equal to 1 if feeder *nf* is selected in the time period *T* of year *y* and 0 otherwise, *pnfloss(T,y)* are the active power losses of feeder n_f in the time period *T* of year *y*, *t(T,y)* is the duration of time period *T* of year *y*, and *LC(T,y)* is the loss cost in *T* of *y*:

$$C^{Loss}(y) = \sum_T\left\{\sum_{n_f}\left[z_{n_f}(T,y)\times p^{loss}_{n_f}(T,y)\times t(T,y)\times LC(T,y)\right]\right\} \tag{15}$$

In equation (16), $C^{tr}(y)$ relates to the total cost of imported energy from the transmission grid in year *y*. *EC(T,y)* is the cost of imported energy from the transmission grid in the time period *T* of year *y* and $p^{tr}(T,y)$ is the imported power from the transmission grid in *T* in year *y*:

$$C^{tr}(y) = \sum_T\left\{EC(T,y)\times t(T,y)\times p^{tr}(T,y)\right\} . \tag{16}$$

Equation (17) illustrates the total network reliability cost $C^R(y)$, where $\lambda(\partial_{nf}(y))$ is the failure rate of line CT per kilometer per year, the number 8,760 is related to the total hours in a year, *CCLF* is the cost of curtailed load per fault, L_{nf} is the length of line n_f, $pf_{nf}(T,y)$ is the power flow of feeder *nf* in *T* and *y*, and $rp(\partial_{nf}(y))$ is the average duration of fault on line CT. *HEC* is the energy cost per hour of fault, Λ^{cl} is the set of all candidate lines, Λf is the set of all network feeders, Υ is the set of time periods, and Ψ is the set of planning years:

$$\begin{aligned} C^R(y) = {} & \sum_{n_f}\sum_T\left[\left(\left(\lambda\left(\partial_{n_f}(y)\right)\times\frac{t(T,y)}{8760}\right)\times CCLF\right)\times L^{n_f}\times pf_{n_f}(T,y)\times z_{n_f}(T,y)\right] \\ & +\sum_{n_f}\sum_T\left[\left(rp\left(\partial_{n_f}(y)\right)\times\lambda\left(\partial_{n_f}(y)\right)\times\frac{t(T,y)}{8760}\times HEC\right)\times L^{n_f}\times pf_{n_f}(T,y)\times z_{n_f}(T,y)\right] \\ & \forall n_{cl}\in\Lambda^{cl}, n_f\in\Lambda^f, T\in\Upsilon, y\in\psi \end{aligned} \tag{17}$$

Equation (18) minimizes equations (14)–(17), where *i* is the discount rate:

$$\min\left\{\sum_y\frac{1}{(1+i)^y}\times\left[C^{upg}(y)+C^{Loss}(y)+C^{tr}(y)+C^R(y)\right]\right\} \tag{18}$$

2.1.12 Switching operations minimization (OF12)

Equation (19) minimizes the total cost due to switching operations in DNR, where SW_c is the switching cost owing to the costs of dispatching technicians in the case of non-automated systems, maintenance requirements, and shortened lifetime of switches. N_{SW} is the total number of switches installed in the distribution system, x_i is the status of the switch *i* after reconfiguration, and x_{io} is the status of the switch *i* before reconfiguration, being equal to 1 for a closed switch and 0 for open:

$$\min SW_{cost} = SW_c\times\sum_{i=1}^{N_{SW}}\left|x_i - x_{io}\right| . \tag{19}$$

2.2 Constraints used for reconfiguration

Several constraints have been included in the DNR. Next, we present the most used constraints functions with metaheuristic algorithms. Here, the term C1 means Constraint 1, C2 means Constraint 2, and so on, representing the terms defined in Table 1.

2.2.1 Power balance (C1)

Power balance can be represented as in (20), where the term *g(x)* represents the power flow, which must be equal to zero:

$$g(x) = 0 . \tag{20}$$

2.2.2 Voltage limits (C2)

The voltage limits of all nodes of the power network can be represented as constraints defined in (21). The term V_{imin} is the minimum value of voltage at node *i*, the term V_{imax} is the maximum value of voltage at node *i*, and the term V_i is the voltage at node *i*:

$$V_{i\min}\le V_i\le V_{i\max} . \tag{21}$$

2.2.3 Branch current threshold (C3)

The current of each line I_l is restricted by the maximum current of each element I_{lmax}, where I_l is the current flowing at the *l*th branch and I_{lmax} is the maximum value of current in branch *k:*

$$I_l\le I_{l\max} \tag{22}$$

2.2.4 Feeding of all loads (C4)

The constraint defined in (23) ensures that the network is radial and all loads are connected, where *A* is the adjacent nodes matrix. Thus, when det(*A*) is equal to 0, the system is not fed completely and when det(*A*) is equal to 1 or −1, all buses are fed:

$$\det(A) = \pm 1 \tag{23}$$

2.2.5 Maximum number of branches (C5)

For radial networks, the number of branches can be obtained as a constraint as shown in (24), where *nbr* is the number of branches and *N* is the total number of nodes:

$$nbr = N - 1 \quad (24)$$

2.2.6 Minimum PMUs installed (C6)
The minimum number of PMUs to install in the power system is calculated according to (24), where $f(x)$ refers to the minimum quantity of units to install:

$$f(x) \geq 1 \quad (25)$$

2.2.7 Maximum allowable daily moving step of LTCs (C7)
The maximum allowable daily moving step of LTCs can be restricted by using (26), where $A_{T \cdot n}$ is the number of steps of the LTC n, $A_{T \cdot n \cdot Max}$ represents the maximum allowable daily moving step of the LTC n with n as the number of the LTC, and N_T is the maximum number of transformers:

$$A_{T \cdot n} \leq A_{T \cdot n \cdot Max}, n \in (1, N_T) \quad (26)$$

2.2.8 Limits for movements of LTCs (C8)
The maximum number of tap changes of each LTC can be restricted by using (27), where S_{nt} represents the current position of the LTC, $S_{n \cdot Max}$ is the highest position of the LTC n with n as the number of the LTC, and N_T is the maximum number of transformers:

$$1 \leq S_{n \cdot t} \leq S_{n \cdot Max}, n \in \left(1, N_T\right) \quad (27)$$

2.2.9 Number of daily switching operations for capacitor banks (C9)
The number of daily switching operations for the capacitor banks can be restricted by using (28), where $A_{C \cdot m}$ represents the number of switching operations of the capacitor bank switch m, $A_{C \cdot m \cdot Max}$ is the maximum allowable daily switching operation number for capacitor banks, m is the capacitor bank switch, and N_C the maximum number of capacitor bank switches:

$$A_{C \cdot m} \leq A_{C \cdot m \cdot Max}, m \in (1 \sim N_C) \quad (28)$$

3 Nature/Evolutionary-inspired algorithms applied to DNR

Figure 1 shows how the selected metaheuristic algorithms (PSO, GA, SA, ACO, IA, and TS) have been used for DNR from 2011 to 2016. The search process was developed in SCOPUS and the ISI Web of Knowledge and considered articles in journals, conferences, and proceedings. Moreover, the keywords used in the searching process were "feeder network reconfiguration," "distribution network reconfiguration," and the name of each algorithm.

Clearly, GA is the most used in the topic as it has been implemented in many topics and its proficiency has been tested for many years. PSO presents a similar behavior considering its maturity in the topic. On the other hand, more recent algorithms are being developed that promise to be good options for future contributions. In addition, there are many more articles in the ISI database than in SCOPUS; however, there are more conference papers registered at SCOPUS than proceedings registered at ISI. The number of results is 438, which can be the same papers, but found in each of the two databases. Furthermore, a same work can be found as a conference and article paper as some events pass their best papers through to publication in an indexed journal.

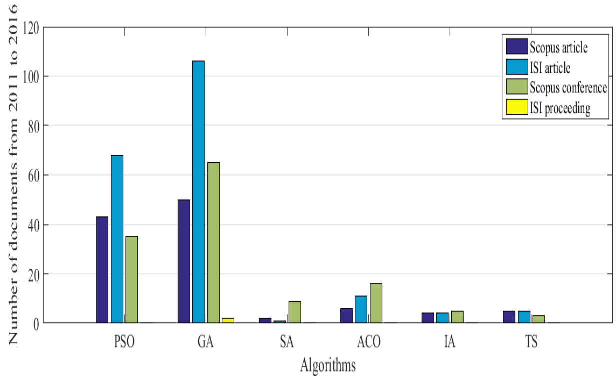

Fig. 1. Number of documents for each algorithm considering SCOPUS and ISI databases from 2011 to 2016

Figure 2 presents a detailed scenario of each metaheuristic algorithm used for DNR per year. From this figure, it can be perceived that in most cases, GA has the bigger contribution followed by PSO. Finally, it is important for academics to consider that the implementation of these techniques is constantly growing due to the need to handle bigger combinatorial problems in real life that cannot be achieved by regular and exact methodologies.

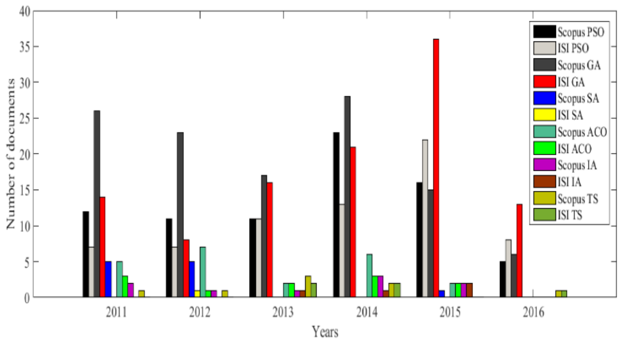

Fig. 2. Detailed number of documents for each algorithm considering SCOPUS and ISI databases

The remainder of this section presents a summary of the most used techniques and the contributions developed in several works, their improvements, and how they have been used.

3.1 Particle Swarm Optimization (PSO)
PSO was developed by PhDs Eberhart and Kennedy in 1995 [109]. It was initially structured to determine mass behavior; however, programmers noted its potential for solving optimization problems. PSO allows solving a problem through the concept of particles represented by insects, birds, and other organisms.

Particles usually transport themselves in big groups to search for food. In a similar way, PSO emulates this behavior as it initializes a population with a number of particles that move in a space of solutions for any problem. Movement velocity, or the capability to jump from one solution to another to get the optima or a very close value, depends on the programmer. There are two determining factors to the orientation of each particle. The first is own experience, denominated as L_{best}, which is the best encountered solution by the particle. Second, it is the global experience, denominated as G_{best}, which is the best solution obtained so far by any particle in the population.

PSO was first designed for continuous problems, but the authors also developed a binary version [110] to solve non-continuous optimization problems, such as for distribution feeder reconfiguration. PSO has been developed using different approaches to improve the search time and avoid local optima. In [97], an Enhanced Integer Coded Particle Swarm Optimization (EICPSO) algorithm was modeled and demonstrated a faster speed than the Genetic Algorithm (GA), Modified Binary Particle Swarm Optimization (MBPSO), and Discrete Particle Swarm Optimization (DPSO) for load-balancing and reconfiguration. Experimental results were obtained from three scenarios. Scenario I was the 33-bus system, where all algorithms reached the optimal value. Scenario II was 94 load zones from the Taiwan Power Company (TPC) system and Scenario III was a modified 188 load zones, also from the TPC system. In the last two systems, EICPSO was shown to be faster than the other techniques; even in the bigger system, it reached the optima when other algorithms could not. Similar approaches are developed in [47], [50], and [57].

Reconfiguration can be used to maximize the injection of Distributed Generation (DG) in a medium- or low-voltage feeder system. In [111], a method was proposed to introduce a proper number of DG units while considering different stochastic scenarios for variable wind speed. Feeder reconfiguration was presented in three test systems (5-, 19-, and 33-bus) while applying a Binary Particle Swarm Optimization (BPSO) algorithm. The results showed that with volt/var control by shunt capacitor, on-load tap changer, voltage regulator, and feeder reconfiguration, DG injection can be maximized. Similar works are presented in [48] and [49].

Other studies were performed by Niknam et al. [30] to work out several scenarios, taking into account the uncertainty of wind speed, power injection by wind turbines, and varying both active and reactive loads. A Weibull–Gaussian probabilistic distribution function was used to identify the scenarios stochastically. The AMPSO (Adaptive Modified Particle Swarm Optimization) algorithm was implemented for the reconfiguration process. To verify its power, evaluations were made with the 33- and 69-bus test systems against other algorithms, such as PSO – Shuffled Frog Leaping Algorithm (PSO–SFLA), PSO-HBMO, Modified SFLA (MSFLA), Honey Bees Mating Optimization (HBMO), GA, and others. The results showed that the proposed algorithm was the fastest. Parallel investigations are offered in [51], [52], and [65].

PSO was also implemented for reconfiguration in the presence of non-linear loads, which cause harmonic distortion. In [112], a methodology is proposed to evaluate the influence of non-linear loads in the reconfiguration process. Two new algorithms were tested against DPSO to recognize convergence velocity and derive accurate solutions: the Imperialist Competitive Algorithm (ICA) and the SFLA. The outcomes show that both are better than DPSO for long- and short-term reconfiguration problems. Comparable results are presented in [64] and [98].

Navy ship power system reconfiguration is performed in [103], where a Small Population Particle Swarm Optimization (SPPSO) algorithm is accomplished. A methodology is proposed to maximize priority loads and the magnitude of loads to be served. A Pareto optimizing front was used to determine the optimal solution. SPPSO varies itself from original PSO in the reduced population of particles and, after a few iterations, particles are regenerated in order to avoid local optima. A similar work is presented in [104].

In [113], a BPSO was worked out to pursue the optimal configurations of 33- and 123-bus radial distribution systems for maximizing reliability and minimizing active power losses. To achieve the fitness function, the authors developed a probabilistic reliability model based on cut sets. Radiality is considered due to its simplicity in protective relay coordination. More multiobjective analyses can be read in [53–56] and [106].

Tolabi et al. [17] investigated the enhancement of three different objective functions: minimizing power losses and improving load-balancing and voltage profile. As a multiobjective problem, a Fuzzy-ACO algorithm was presented and compared with Fuzzy-PSO and Fuzzy-GA. The results showed that Fuzzy ACO achieved optimal values for the 33-bus test system and the 84-bus TPC system. Other investigations concerning PSO are found in [76–79].

Nasir et al. used PSO to minimize active power losses and voltage profile improvement by implementing the process as a multiobjective function [27]. The authors evaluated three cases: 1) reconfiguration only; 2) reconfiguration with DG allocation and sizing; and 3) the same as case 2, but considering buses with the lowest voltages obtained at case 1 in order to place DG. The test case was the 33-bus radial test feeder. The experiments showed that case 3 had a better result than the other two cases, but it has to be noted that a DG unit cannot be installed in all evaluated scenarios.

Sulaima et al. integrated Evolutionary Programming (EP) and PSO to develop a Modified Evolutionary PSO (EPSO) in [40]. The contribution of this algorithm is that in every single iteration, both old and new particles are combined and subjected to a tournament selection. Best positions get a bigger probability to gain the tournament and obtain a higher position in the ranking of solutions in that iteration. The highest positioned option is then checked for convergence of PSO conditions. The fitness function was reduction of power losses. This method was analyzed in a 69-bus test feeder against PSO and regular EPSO, providing better results in minimizing power losses. Other PSO adaptations are in [80].

3.2 Genetic Algorithm (GA)

The GA has been used for several applications. It was first developed by Holland in his Doctoral thesis [114]. In reconfiguration problems, it is an adaptive and good choice for finding an optimal or near-optimal value. Some cases are mentioned below.

Tomoiagă et al. designed a GA based on connected graphs using branch lists instead of an adjacency matrix [43] because the latter is almost full of zeros. To get a good initial "chromosome," an ecological niche method was used and a sharing function was implemented for determining the selection operator of the algorithm. The crossover operator was made thanks to a cyclomatic number, which guarantees that only one element is changed for each loop of the system. Finally, in the case where a non-radial configuration was found, both mutation and inversion operators were inserted to ensure that all loads would be fed. The proposed algorithm was tested in five test systems (16-bus and three-feeder system, 33-bus system, 70-bus system, 69-bus and two-feeder system, and an 83-bus and two-feeder system). Similar approaches are developed in [47] and [58].

Electricity companies require designs that allow them to take a decision with good forecast. The methodology developed in [115] contains a study with long-term conditions. Distributed generation and reconfiguration are introduced together in order to improve the state of the system and also to reduce CO_2 emissions and investment costs. This is why the Non-Dominated Sorting Genetic Algorithm (NDSGA) proposed by the authors deals with multiobjective and multi-year problems. Moreover, uncertainties about wind, solar, and load profiles were manifested in the paper as it would be the method more applicable to real companies. This algorithm was proved in two power systems: the 38-bus test system and 119-bus test system. Similar approaches are shown in [57] and [63].

Eldurssi and O'Connell expanded the NSGA with a new approach in [19]. The Fast Non-Dominated Sorting Guided Genetic Algorithm (FNSGA) enables working with multiobjective functions directly or assigning values to each function as determined by the operator. This algorithm uses guided mutation instead of a random one, which allows the elimination of "bad" chromosomes (non-radial configurations) and guarantees that the next generation will maintain good solutions. This algorithm was tested in three systems (16-bus test system with three feeders, 69-bus test system, and a real 136-bus test system from a Brazilian distribution system), showing the accuracy and speed of the proposed method. Similar methodologies are followed in [59] and [108].

A study of a real-life scenario at ACEA Distribuzione in Italy was developed by Luca et al. in [116] that utilized a GA for the integration of DG units in a small smart grid. It is considered that real networks must be updated constantly; thus, this approach focused on making a comparison between time-constraint (TC) and time-unconstraint (TU) scenarios based on the daily load curve and significant changes in load and PV generation profiles from hour to hour. The TC scenario demands the algorithm get a solution in a period of 1 h, whereas TU does not have that constraint. The results showed that GA could be used for a time-constraint setting due to the differences between TC and TU problems being not too large. The problem was established for reducing active power losses. Some similar results are identified in [81], [82], and [83].

Feeder distribution reconfiguration was used with the assistance of a GA and the matrix of adjacency for selecting feasible configurations in [117]. The authors proposed a roulette wheel methodology for choosing the chromosome (i.e., the open/closed status of switches in the network). The objective function was to minimize the total cost of purchased energy, taking into account the status of switches, tap positions of transformers, and the power factor of DG units. The algorithm was tested in a 16-bus modified system and a real Iranian 204-bus system. The results showed that when reducing purchased energy cost, the operation costs are also diminished. Similar outcomes were achieved in [60] and [61].

The GA is also used for reducing both the Customer Average Interruption Duration Index (CAIDI) and Customer Average Interruption Frequency Index (CAIFI) by changing the topology of the distribution system. Do Nascimento et al. proposed in [118] an effective manner to restore service to customers while a fault occurs in the feeder, supporting a DG installed for industrial plants such as Co-Generation. The GA works as follows: the chromosome selection process is made in a random manner. The crossover operation guarantees that any chromosome may suffer a change when in combination with any other chromosome. This process is also random. Finally, a mutation process is required to allow differences among the best options' offspring. The test system used was the real scenario of AES Eletropaulo with hydro turbines, steam turbines, and the power grid. Other works related to GAs are in [107].

Kanwar et al. performed three improved metaheuristic techniques in [24]: GA, PSO, and Cat Swarm Optimization (CSO). The Improved GA, PSO, and CSO follow some of the rules established by the authors to avoid local trapping, which derives local, but not global optima. The CPU time is also reduced because the first solution is guided to a better fitness function value. The algorithms were proved on IEEE 33- and 69-bus systems to determine shunt capacitor and distributed generation allocation first and, after that, reconfiguration to maximize the percentage of energy reduction. In all simulations, the improved algorithms obtained better results than the originals, with faster convergence. Similar developments are in [62] and [99].

Sultana and Roy used the Opposite Krill Herd (OKH) algorithm to solve the problem of optimal capacitor location and feeder network reconfiguration together [41]. The proposed method describes the behavior of krill herds when moving toward food and when predators are close. The authors compared its proposal with the original Krill Herd (KH) algorithm and with two other techniques (Non-dominated Sorting Genetic Algorithm and Fuzzy multiobjective approaches). Finally, the proof was carried out using IEEE 33- and IEEE 69-bus test systems in three scenarios: constant power, constant current, and constant impedance. Each scenario was developed in the presence of a rated load and a stress load. The results showed that OKH has better performance and accuracy than the other techniques.

Shamsudin et al. developed a Selection Improvement GA (SIGA) that includes reassembly processes [36]. In this paper, a string is created to compare the results found by each chromosome in every single iteration that allows sorting the results according to the fitness objective (power losses and voltage profile) evaluation, giving a reasonable way to do the selection because the best evaluated has a bigger probability to acquire descendants. The SIGA is compared with GA in eight cases as defined by the values of both crossover and mutation operators. SIGA presented better results than GA in accuracy for the 33-bus radial test feeder. A similar methodology was presented in [35], where the selection process is carried out thanks to the roulette wheel, but there is a re-ranking process of the solutions acquired at each iteration, which gives the fittest ones a bigger change to have offspring. Other papers that deal with this topic are [46], [100], and [105].

3.3 Simulated Annealing (SA)

Simulated Annealing is a technique that mimics a particular phenomenon whereby liquids freeze and metals recrystallize in the process. It takes the probability of a particle to pass from a lower energy to a higher energy state while considering its temperature. It was proposed initially by Kirkpatrick, Gelatt, and Vecchi in 1983 [119].

Olamei et al. published their paper [32] proving a hybrid ACO-SA (Ant Colony Optimization – Simulated Annealing)-based metaheuristic technique to solve both the reconfiguration and sizing problems of DG units. The process started by selecting the vector positions using ACO.

Then, the selection of new positions was realized upon SA. Finally, through ACO, convergence was tested. The algorithm was used in a real 31-bus system connected to three substations and three DG units. The topology could be changed because there were four tie switches. A comparison with ACO, PSO, TS (Tabu Search), DE (Differential Evolution), and GA, show that ACO-SA provided the best solutions. Similar approaches are presented in [84].

Nournejad et al. used SA and GA to compare results obtained from a VSHDE (Variable Scaling Hybrid Differential Evolution) algorithm applied to a feeder network reconfiguration in [31]. VSHDE is an effective method for avoiding the main drawback of HDE, which is a fixed scaling factor that produces possible local optima instead of the global one. To make it variable, the authors used the one-fifth rule for determining the current value of the factor in each iteration. This algorithm was tested on a 16-bus system with three feeders and a 33-bus system from the TPC. The results showed that VSHDE is more accurate and has better performance than GA and SA.

Chen et al. mixed concepts from SA and Immune (SAI) algorithms to avoid local stagnation in [95]. The objective function was to reduce power losses in distribution systems. The authors proposed to encode the topology into loops and apply the branch exchange method for limiting the code to feasible options. This allows the algorithm to be fast. They used the Immune algorithm for shaping the genes and mutating them when needed. The selection process was based upon SA equations, taking into account the temperature (fitness function) of each element. Finally, they used a vaccine and inoculation-based method to determine the dominant gene. This technique was compared with a Fuzzy GA, demonstrating that SAI has better performance. The test system was an IEEE 69-bus system.

Samui et al. studied the planning problem for radial distribution systems using a direct approach derived from the principle of optimality in [11]. They proposed an algorithm that searches an optimal path between the main substation and the farthest load node. If any previous node is encountered in such a path, then it is not necessary to search any other path to feed that node. Nodes that are not covered by those paths must receive a similar procedure. This algorithm was proved on two systems, a 25-bus system and a 51-bus system, with four different substations. In the last one, they contemplated the possibilities of not having all the substations connected. Results were compared with SA, GA, and ACO (Ant Colony Optimization), finding similar results with minor time consumption.

Nie et al. integrated SA coded in MATLAB language and a power simulation program called Open Distribution Simulator Software (OpenDSS) in [29]. The authors' purpose was to evaluate the real power losses in a distribution system in normal operation subject to different load levels with DG and a post-fault behavior for localizing paths in order to power every load in the presence of DG. It was possible in a 33-bus test system, where power loss values decreased and restoration possibilities after the fault were found, when DG are installed in the network.

Farahani et al. proposed an improved reconfiguration method concerning a simple branch exchange, mixed with GA and SA, for both reconfiguration and capacitor location problems in [100]. The authors determined to search for loop sequences first by applying the branch exchange-based method. They then used two different methods for comparison, namely, GA and SA. When loop sequences were obtained, both GA and SA looked for the optimal placement and reactive power magnitude of the capacitor units. This approach was tested on a real two-feeder 77-bus system upon different load levels and a time-varying loads. GA returned more effectiveness than SA due to its minor time consumption and accuracy.

Bruno et al. presented interesting results from a smart grid project developed on the real power distribution systems of two distribution companies in Italy [18]. A Simulated Annealing-based method was used to determine the optimal configuration of feeders in both planning and operation modes. This project worked from a SCADA framework, which allows data acquisition and control of the whole system. Fitness functions and constraints were checked on an OpenDSS simulator and SA was performed using MATLAB code. The purpose was to determine the amount of power injected from the DG without violating the technical limits and time restriction. The results were confirmed from a real system based on 11 feeders, two transformers from the main substation, and 930 buses.

Kritavorn et al. worked on a Simulated Annealing approach in [25] for minimizing active power losses in distribution systems using both reconfiguration and DG location-sizing. They proposed a 69-bus test system for validating the effectiveness of the SA algorithm. All branches were considered as sectionalizing switches. The results demonstrated that both reconfiguration and DG can diminish power losses, thereby saving energy production costs.

3.4 Ant Colony Optimization (ACO)

Ants use pheromones to communicate with each other in order to get food to the nest. The decision to choose a path depends on the amount of pheromones located on it and the evaporation rate [17].

A Fuzzy-ACO algorithm is proposed in [17], where the principles of fuzzy logic are applied to make the Ant Colony algorithm more efficient. The algorithm is used in multiobjective problems such as loss reduction, voltage profile improvement, and load-balancing index reduction in a distribution system. Five test scenarios are proposed: the base case; reconfiguration only; reconfiguration and PV allocation; reconfiguration and DSTATCOM allocation; reconfiguration with PV allocation; and DSTATCOM allocation. Experiments were worked out on a 33-bus test system and a real 11-feeder TPC system. Results showed that reconfiguration with PV allocation and DSTATCOM allocation is optimal, and these were compared with Fuzzy-PSO and Fuzzy-GA, getting a better performance with Fuzzy-ACO. Similar results are presented in [85].

Wu et al. proposed an Ant Colony Search (ACS) algorithm to optimize distribution networks [9]. The novelty in this paper involves heuristic techniques for updating the global pheromone matrix, allowing to exploit as many solutions as possible. Fitness functions were defined to be loss reduction and load-balancing index improvement, considering DG penetration. The experiments were developed on a 33-bus test system and a real TPC distribution system. The proposed method was compared with AS and GA and obtained better performance with the ACS algorithm than with the other ones, which demonstrates that DG contributes to improving the grid. Similar works are presented in [66] and [68].

ACO has been improved as researchers make some adaptations by introducing other techniques. In [33], Saffar et al. presented a Fuzzy-ACO to solve a multi-variable problem, namely, power losses reduction and load balance improvement. The optimization is performed using weighting factors and membership functions in order to make the single functions above compatible. The pheromone updating process was worked out considering the resistance and voltage drop on each branch. The method was tested on both modified IEEE 33-bus and 69-bus distribution systems and compared with GA, Refined GA (RGA), Fuzzy, heuristic techniques, SA, and Plant Growth Search (PGS), returning the best results for the multi-variable function. Other works are developed in [67] and [84].

Swarnkar et al. used Heuristic Spark (HS) to focus the ants selecting only feasible solutions, considering several vectors that avoid loops and islands [42]. This algorithm is named "Adapted ACO" (AACO) based on the use of heuristic techniques. With such implementation, the algorithm is able to select only trees to evaluate the fitness function, which is power losses reduction. Once a solution is reached, it must be compared with previous solutions to determine their similitude; if they are the same, then a power flow algorithm is not necessary to be run because the answer will be the same. The above contributions let the algorithm find an optimal solution in less time. It was proved with 33-, 70-, 83-, 119-, 136-, and an unbalanced 33-bus systems, and compared with other metaheuristic and heuristic techniques, such as GA, RGA, HBMO, Heuristics, SAPSO, AIS, MSFLA, and ITS, getting better results or, in some cases, the same, but the efficiency was always better. Other works related to ACO are reported in [88].

Abdelaziz et al. introduced the Hyper-Cube (HC) framework to the ACO algorithm for solving the reconfiguration problem of distribution systems [91]. The HC-ACO uses the transition states for updating the amount of pheromones at each iteration, maintaining the maximum value of pheromone as unity while that branch is part of the solution at every iteration. The proposed method was implemented in the 33-, 69-, and 118-bus test systems. A comparison was made in the 69-bus test system, where three different scenarios were proposed: light, normal, and heavy load. In all testing, HC-ACO obtained the same results as SA, TS, Modified TS (MTS), and MPSO, but was less time-consuming. Similar methodologies are followed in [87].

Scenna et al. identified a wide range of Ant Search algorithms in [34]. According to transition rules, virtual ants are guided considering heuristic movements. Two important parameters are the pheromone updating and the desirability to choose a path. Such desirability is considered the inverse of branches' resistance as it is a direct parameter to calculate power losses. ACO was proved against several heuristic techniques, providing the same or better results with an improvement in efficiency as reflected in the reduced time. The systems used were the 33- and 69-bus test systems.

Ahuja et al. [93] used the pheromone updating strategy of ACO and the crossover operator from GA to implement a Pheromone-Based Crossover Operator to the distribution power grid reconfiguration problem. Real losses reduction was selected as a single fitness function. The crossover operator guarantees the exploration–exploitation balance in order to avoid local minima and to search around the best combinations, a concept derived from elitism. The 86-, 94-, 136-, and 201-bus systems were used to demonstrate the effectiveness of the algorithm in medium- and large-scale systems. It was also compared with a uniform crossover algorithm and other heuristic techniques, obtaining similar results in medium-scale systems, but a better performance and accuracy in large-scale systems. Other works are in [86].

Abdelsalam et al. performed an analysis on the intermittent PV and wind turbine variables, such as solar irradiance and wind velocity, in distributed generation connected to a distribution power system in [92]. The scope of this research is to determine the optimal location of PMUs (phasor measurement units) in distribution power systems considering reconfiguration. ACO is used in reconfiguration, taking into consideration the intermittence of distributed generators. A Greedy Algorithm is used for locating the PMUs properly based on the reconfiguration process. The IEEE 33-bus test system was selected to develop experiments. The analysis demonstrates that PMUs are necessary for visualization of power systems and, according to the topology of power grid, more or less PMUs are required.

Mehfuz and Rashid used the ACS algorithm to reduce active power losses in distribution systems [26]. Following the behavior of ants to search food, the algorithm is capable to find an optimal or close configuration of the power grid that reduces active power losses. The ACS was compared with the Artificial Bee Colony Algorithm (ABCA), SA, Differential Evolution (DE), GA, and MGA in IEEE 14- and 16-bus test systems. The results demonstrate the accuracy and efficiency of the proposed method.

Meng et al. [45] proposed a bi-level programming scenario using ACO for up-level and GA for low-level. The scope of the paper is to diminish the switching operations and reduce power losses. The ACO algorithm worked out the reconfiguration of the grid in a first stage while the GA optimized the scheduling of DG-controllable units, such as wind turbines, PV arrays, and micro turbines moved by fuel. This method demonstrates in a modified IEEE 33-bus test system that the amount of switching operations can be reduced if DGs are available. Markov chains estimated DG power input. Other results are presented in [89].

3.5 Immune Algorithms (IA)

Immune algorithms are nature-inspired in that they mimic the behavior of genes and antibodies while defending the human body from viruses and infection or bacteria [44,120].

In [44], an Improved Immune Genetic Algorithm (IIGA) is proposed to reduce active power losses in distribution networks. An encoding strategy is made to select only feasible solutions because distribution power grid reconfiguration must maintain a radial structure: such a methodology is called a "fundamental loop." To prevent premature convergence into a local optimal solution and speed up the convergence, hypermutation and immune operators, such as vaccine pool, are addressed. Finally, a tournament operator with parent offspring competition is introduced. The IIGA was proved on the 33- and 69-bus test systems against GA, hybrid PSO, GA, and derivations of the same. The results demonstrated that IIGA has an excellent efficiency and performance. Similar works are established in [74].

Belkacemi and Feliachi [120] developed research based on multi-agent systems for power system reconfiguration and restoration. It was designed as a multi-level scenario. Mimicking the thymus in the human body, a master agent located at the substation level conducts the whole system while other agents (same as T-lymphocytes) are delivered to the system: student agents, load agents, node agents, and DG agents. Each agent has a particular task: to open/close a branch, to shed/feed a load, or to change the topology of the system. A neural network was used to learn about viruses and bacteria, which are represented by faults and voltage profile violations. This approach allows the Multi-Agent System (MAS) to make smart decisions. To demonstrate its effectiveness, it was implemented on the Southern California Edison's Circuit, known as the Circuit of the Future. The case simulated was a fault that isolated a load and the MAS was capable of restoring power to it by reconfiguring the grid.

An Immune GA was presented by An et al. in [94] to solve the feeder network reconfiguration problem while reducing real power losses. In this paper, GA concepts are joined with some features of the human immune system when defending the body against antigens. Those features are the production of antibodies, affinity and density for memory of cells, and promotion and suppression of antibody production, depending on the fitness value of each antibody (system configuration). Population updating was considered the same as in normal GA. Additionally, a loop-based procedure was integrated to avoid unfeasible solutions. Simulations are carried out on the IEEE 33-bus test system, comparing the initial configuration with the optimal one and without a comparison to other algorithms. Similar methods are followed in [69] and [70].

Wang et al. [96] established a hybrid Immune-Based Co-Tabu Search Algorithm (ICTSA) proposal, which is between the Co-TS and Multi-Agent Immune-Based algorithms. Initially, it describes two types of organisms, antigens, and antibodies. The objective function is minimization of active power and constraints are considered the antigens (bacteria or viruses), whereas the candidates for good solutions are considered the antibodies. The antibodies are selected through the implementation of a tabu search process. The affinity function and its maturation from IA was used to update/change the combinations. The IEEE 33-bus test system was addressed to verify the effectiveness of the proposed algorithm. It was compared with Clonal GA (CGA) and Immune CGA (ICGA), gaining better results for ICTSA in time consumption and minimization of active power. Other hybrid algorithms can be found in [71].

A hybrid Simulated Annealing Immune (SAI) algorithm was presented in [95]. Chen et al. considered a loop-encoding method to avoid unfeasible solutions for the radial reconfiguration problem. The main objective is minimization of real power losses. The algorithm initializes the process using stochastic steps based on immunology to generate initial genes (solutions). Hypermutation is accomplished before selecting the initial temperature, and the Boltzmann constant from the SA operator is calculated to eliminate degeneration. Concepts of vaccination and inoculation are applied later to construct the next generation. This algorithm was tested on the IEEE 69-bus test system and compared with a Fuzzy-GA, obtaining the same results, but with faster performance considering SAI.

Gu et al. [21] presented an improvement of GA considering the benefits of immunity. An Immune GA (IGA) is proposed that avoids premature convergence and local stagnation with the aid of an immune memory function, antibody diversity keeping function, and self-regulating function. This loop-based methodology was considered to escape from isolated and non-radial configurations. Power loss minimization was selected as the objective function. An IEEE 33-bus test feeder was used to verify the feasibility of the approach, obtaining better results against GA in reducing losses and improving the voltage profile.

An Artificial Immune Network for Combinatorial Optimization (Copt-aiNet)-based and Artificial Immune Network for Optimization (Opt-aiNet) approach was used in [39] to solve the reconfiguration problem. It uses the fundamental loop theory to avoid non-radial configurations and a backward/forward sweep-based method to evaluate affinity, which is the objective function (power losses). The concepts of hypermutation, memory of antibodies, meta-dynamic processes, strong and weak mutations, and clonal processes are considered to achieve the optimal solution. These two algorithms were tested on five different systems as the 33, 70, 84, 119, and 136 nodes along with a real one with 417 nodes. The results were compared with those obtained in specialized literature and found to be the same, with the real system offering a better result. Copt-aiNet was demonstrated to be faster than Opt-aiNet. Other papers referring this topic are in [72] and [75].

3.6 Tabu Search (TS)

The Tabu Search is a metaheuristic technique developed by Glover [121,122]. This technique aims to emulate the human mind in order to avoid repeating previous configurations or events. The process of the algorithm has a tabu list that registers all the events or configurations evaluated before, a configuration space where the possible solutions are located (space of solution), and an aspiration criterion that allocates the best solution in the first line of the tabu list; however, if there is an improvement in other iterations, then it has to be moved. Some contributions to distribution power grids are listed below.

Abdelaziz et al. [16] proposed a Modified TS (MTS) that consists of a variable-sized tabu list to escape from local minima. Besides, a constrained multiplicative move is also used to avoid local minima. This approach allows the algorithm to exchange branches in a multilevel manner and explore the vicinity. An incidence matrix is implemented to guarantee a radial topology. The objective function is real power losses reduction in feeders. Finally, the algorithm is tested on three distribution systems: 16-, 69-, and 119-bus test feeders. In the case of the 69-bus feeder, three different scenarios are analyzed: normal, heavy, and light loads. The effectiveness is proved against SA, GA, Artificial Networks, and hybrid approaches between them, thus demonstrating the accuracy of the proposed method. Similar approaches are made in [73].

A comparison among binary coding, decimal coding, and loop-based decimal coding schemes is presented in [38] to determine the least time–consuming and most effective and optimized feeder network reconfiguration. The loop-based decimal coding scheme improves the speed of convergence and avoids unfeasible solutions (non-radial configurations). The Tabu Search is used in the optimization process and is simulated on a 69-bus feeder system, providing a better result than the initial state. No comparisons are presented. In [37], the authors continued the research presented in [38] by introducing capacitor placement. Similar results are obtained when loop-based encoding is applied to avoid unfeasible configurations. A Tabu Search-GA algorithm was introduced in the same way as before to solve the optimization problem. Again, the test system was the 69-bus test feeder.

Franco et al. integrated a TS algorithm using several approaches to reduce time consumption and minimize power losses in distribution power systems [20]. A loop analysis is introduced that initially considers the tie switch in a loop and classifies the sectionalized switch into one of two groups: the right-positioned group or the left-positioned group. Doing so, the neighborhood can be reduced to only feasible configurations. Additionally, an approximate calculation of objective function is introduced to reduce the number of complete power flows. A reduction of neighbors is implemented, which limits branch exchange to the nearest branches positioned close to the tie switch until a higher objective function value is found. This reduces the time expended by the method to find the optimal solution. This method is compared with others presented in the literature as other TS and heuristics, obtaining the same or better results, but always with less time consumption. The test systems where this method is proved are the 33-, 84-, 119-, and 136-bus systems.

Garcia and Espinosa used a TS algorithm to solve the reconfiguration problem in a reduction of voltage sag events presented during one year in a distribution system [101]. Two approaches are performed for analyzing voltage sag events. In the first scenario, a threshold of events is considered independently to each bus, whereas in the second scenario, the same threshold of events was considered to all buses. Three-phase faults were selected for analysis. The voltage limit to determine a voltage sag was 0.8 pu. The reconfiguration was worked out only when the number of events was above the threshold. To prove the effectiveness of the method, the IEEE 57-bus test feeder is used, obtaining reductions when reconfiguration is developed.

Garcia and Espinosa continued the work presented in [101] by applying an extension in [102]. In this work, the scenario where each bus has a threshold of voltage sag SARFIx is considered, which is the number of sags presented in a bus, group of buses, or the whole system. The difference is to consider both three-phase- and single-phase-to-ground faults in the analysis. TS is used to enhance the reconfiguration process, thereby minimizing the SARFIx index. The sag prediction method is proposed by Espinosa and Hernandez in [123]. This time, 57- and 118-bus test systems are used to demonstrate the effectiveness of the proposal.

Hemdan et al. analyzed the growing behavior of DG in distribution power grids in Germany in [22]. A real feeder network, provided by local utility VDEW (Verband der Elektrizitätswirtchaft), is studied to reduce the annual energy losses in the presence of DGs. To reduce losses, reconfiguration is made by TS algorithm using aspiration while a tabu configuration presented a better solution than the best so far in the tabu list, and diversification, that allows the change of the process when no convergence is found in Tabu list configurations. The units considered by the operator are Combined Heat and Power (CHP) plants and PV arrays. The scenarios evaluated were classified into seasons and different kinds of days (e.g., sunny, rainy, and windy). In addition, a constant injection at different levels of PV was taken into account along with a forecasting evaluation of the PV profile. The load profile was defined by VDEW as residential or commercial. Results showed that the methodology can be used for any utility to reduce annual energy losses. The authors performed a forecasting analysis for different loads. Other works concerning TS are developed in [90].

4 Conclusions

This paper presented a review of some metaheuristic techniques used for solving the DNR problem. A brief description of PSO, GA, SA, ACO, IA, and TS is included. The most recent and relevant papers are summarized to provide a base from which researchers can start their investigations and to focus on the results they hope to get. A timeline was also presented to verify that metaheuristic techniques are used nowadays because of their velocity of convergence and accuracy in finding the optimal solution of reconfiguration problem.

To summarize, most research papers treat the fitness function as power minimization and voltage profile improvement, whereas other papers examine voltage sag and load-balancing indices among other functions. The most used constraints are power balance, node voltage limits, branch current limits, radiality that can be achieved with a detailed number of branches, and an incidence matrix that maintains all fed loads. GA is the most used metaheuristic followed by PSO. Other techniques, such as SA, ACO, IA, and TS, are applied less for network reconfiguration. More recent algorithms, such as Cuckoo Search [23], Bacterial Foraging Algorithm [124], Bat Algorithm [125], and hybrid developments are growing and promise to be good options for future contributions.

It is necessary to develop new approaches in order to make these techniques faster as power systems expand and technologies advance. Faster techniques will allow network operators to act for continuous improvement. Researchers have very good options in the path of systems optimization. It is expected that the implementation of these algorithms will progress due to their effectiveness and speed.

Acknowledgements
This work was supported by the Colombian Administrative Department of Science, Technology and Innovation (Departamento Administrativo de Ciencia, Tecnologia e Innovacion) COLCIENCIAS [grant - Call 617] and Universidad del Norte [grant UN-OJ- 2014-24133].

References

[1] Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, and R. Seethapathy, “Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization,” *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 360–370, Feb. 2010.
[2] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “Analytical strategies for renewable distributed generation integration considering energy loss minimization,” *Appl. Energy*, vol. 105, pp. 75–85, 2013.
[3] D. Q. Hung, N. Mithulananthan, and R. C. Bansal, “Analytical Expressions for DG Allocation in Primary Distribution Networks,” *IEEE Trans. Energy Convers.*, vol. 25, no. 3, pp. 814–820, Sep. 2010.
[4] D. D. Wu, M. Junjie, W. Yulong, and L. Yang, “Size and Location of Distributed Generation in Distribution System Based on Immune Algorithm,” *Syst. Eng. Procedia*, vol. 4, pp. 124–132, 2012.
[5] D. Zhang, Z. Fu, and L. Zhang, “Joint Optimization for Power Loss Reduction in Distribution Systems,” *IEEE Trans. Power Syst.*, vol. 23, no. 1, pp. 161–169, Feb. 2008.
[6] G. Naik, D. K. Khatod, and M. P. Sharma, “Optimal Allocation of Distributed Generation in Distribution System for Loss Reduction,” in *International Proceedings of Computer Science and Information Technology IPCSIT*, 2012.

[7] A. K. Singh and S. K. Parida, "Selection of load buses for DG placement based on loss reduction and voltage improvement sensitivity," in *2011 International Conference on Power Engineering, Energy and Electrical Drives*, 2011, pp. 1–6.

[8] L. Ramesh and S. Chowdhury, "Minimization of power Loss in distribution networks by different techniques," *Int. J. Electr. Electron. Eng.*, vol. 2, pp. 521–527, 2009.

[9] Y.-K. Wu, C.-Y. Lee, L.-C. Liu, and S.-H. Tsai, "Study of Reconfiguration for the Distribution System With Distributed Generators," *IEEE Trans. Power Deliv.*, vol. 25, no. 3, pp. 1678–1685, Jul. 2010.

[10] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, "Power Loss Minimization in Distribution System Using Network Reconfiguration in the Presence of Distributed Generation," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 317–325, Feb. 2013.

[11] A. Samui, S. Singh, T. Ghose, and S. R. Samantaray, "A Direct Approach to Optimal Feeder Routing for Radial Distribution System," *IEEE Trans. Power Deliv.*, vol. 27, no. 1, pp. 253–260, Jan. 2012.

[12] a. R. Jordehi, "Optimisation of electric distribution systems: A review," *Renew. Sustain. Energy Rev.*, vol. 51, pp. 1088–1100, Nov. 2015.

[13] S. Kalambe and G. Agnihotri, "Loss minimization techniques used in distribution network: bibliographical survey," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 184–200, Jan. 2014.

[14] R. J. Sarfi, M. M. a. Salama, and A. Y. Chikhani, "A survey of the state of the art in distribution system reconfiguration for system loss reduction," *Electr. Power Syst. Res.*, vol. 31, no. 1, pp. 61–70, Oct. 1994.

[15] L. Tang, F. Yang, and J. Ma, "A survey on distribution system feeder reconfiguration: Objectives and solutions," in *2014 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA)*, 2014, pp. 62–67.

[16] A. Y. Abdelaziz, F. M. Mohamed, S. F. Mekhamer, and M. A. L. Badr, "Distribution system reconfiguration using a modified Tabu Search algorithm," *Electr. Power Syst. Res.*, vol. 80, no. 8, pp. 943–953, Aug. 2010.

[17] H. Bagheri Tolabi, M. H. Ali, and M. Rizwan, "Simultaneous Reconfiguration, Optimal Placement of DSTATCOM, and Photovoltaic Array in a Distribution System Based on Fuzzy-ACO Approach," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 210–218, Jan. 2015.

[18] S. Bruno, S. Lamonaca, M. La Scala, and U. Stecchi, "Integration of optimal reconfiguration tools in advanced distribution management system," in *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, 2012, pp. 1–8.

[19] A. M. Eldurssi and R. M. O'Connell, "A Fast Nondominated Sorting Guided Genetic Algorithm for Multi-Objective Power Distribution System Reconfiguration Problem," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 593–601, Mar. 2015.

[20] J. Franco, M. Lavorato, M. J. Rider, and R. Romero, "An efficient implementation of tabu search in feeder reconfiguration of distribution systems," in *2012 IEEE Power and Energy Society General Meeting*, 2012, pp. 1–8.

[21] C. Gu, J. Ji, and L. Liu, "Research of immune algorithms for reconfiguration of distribution network with distributed generations," in *The 26th Chinese Control and Decision Conference (2014 CCDC)*, 2014, pp. 2156–2160.

[22] N. G. A. Hemdan, B. Deppe, M. Pielke, M. Kurrat, T. Schmedes, and E. Wieben, "Optimal reconfiguration of radial MV networks with load profiles in the presence of renewable energy based decentralized generation," *Electr. Power Syst. Res.*, vol. 116, pp. 355–366, Nov. 2014.

[23] E. Herazo, M. Quintero, J. Candelo, J. Soto, and J. Guerrero, "Optimal power distribution network reconfiguration using Cuckoo Search," in *2015 4th International Conference on Electric Power and Energy Conversion Systems (EPECS)*, 2015, pp. 1–6.

[24] N. Kanwar, N. Gupta, K. R. Niazi, and A. Swarnkar, "Improved meta-heuristic techniques for simultaneous capacitor and DG allocation in radial distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 653–664, Dec. 2015.

[25] P. Kritavorn, T. Lantharthong, and N. Rugthaicharoencheep, "The combined loss reduction approach to apply in distribution system with distribution generation," in *TENCON 2014 - 2014 IEEE Region 10 Conference*, 2014, pp. 1–5.

[26] S. Mehfuz and F. Rashid, "Ant colony system algorithm for optimal network reconfiguration," *Int. J. Comput. Intell. Syst.*, vol. 7, no. 5, pp. 973–978, Sep. 2014.

[27] M. N. M. Nasir, N. M. Shahrin, M. F. Sulaima, M. H. Jali, and M. F. Baharom, "Optimum network reconfiguration and DGs sizing with allocation simultaneously by using particle swarm optimization (PSO)," *Int. J. Eng. Technol.*, vol. 6, no. 2, pp. 773–780, 2014.

[28] T. T. Nguyen and A. V. Truong, "Distribution network reconfiguration for power loss minimization and voltage profile improvement using cuckoo search algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 68, pp. 233–242, Jun. 2015.

[29] S. Nie, X.-P. Fu, P. Li, F. Gao, C.-D. Ding, H. Yu, and C.-S. Wang, "Analysis of the impact of DG on distribution network reconfiguration using OpenDSS," in *IEEE PES Innovative Smart Grid Technologies*, 2012, pp. 1–5.

[30] T. Niknam, A. Kavousifard, and J. Aghaei, "Scenario-based multiobjective distribution feeder reconfiguration considering wind power using adaptive modified particle swarm optimisation," *IET Renew. Power Gener.*, vol. 6, no. 4, p. 236, 2012.

[31] F. Nournejad, R. Kazemzade, and A. S. Yazdankhah, "A multiobjective evolutionary algorithm for distribution system reconfiguration," in *16th Conference on Electrical Power Distribution Networks (EPDC)*, 2011, pp. 1–7.

[32] J. Olamei, T. Niknam, A. Arefi, and A. H. Mazinan, "A novel hybrid evolutionary algorithm based on ACO and SA for distribution feeder reconfiguration with regard to DGs," in *2011 IEEE GCC Conference and Exhibition (GCC)*, 2011, no. 2, pp. 259–262.

[33] A. Saffar, R. Hooshmand, and A. Khodabakhshian, "A new fuzzy optimal reconfiguration of distribution systems for loss reduction and load balancing using ant colony search-based algorithm," *Appl. Soft Comput.*, vol. 11, no. 5, pp. 4021–4028, Jul. 2011.

[34] F. Scenna, D. Anaut, L. I. Passoni, and G. J. Meschino, "Reconfiguration of electrical networks by an Ant Colony Optimization algorithm," *IEEE Lat. Am. Trans.*, vol. 11, no. 1, pp. 538–544, Feb. 2013.

[35] N. H. Shamsudin, N. a Abidullah, a R. Abdullah, M. S. Mamat, and M. F. Sulaima, "A new technique for the reconfiguration of radial distribution network for loss minimization," *Int. J. Eng. Technol.*, vol. 6, no. 5, pp. 2488–2495, 2014.

[36] N. H. Shamsudin, N. F. Omar, M. F. Sulaima, H. I. Jaafar, and A. F. A. Kadir, "The Distribution Network Reconfiguration Improved Performance of Genetic Algorithm Considering Power Losses and Voltage Profile," *Int. J. Eng. Technol.*, vol. 6, no. 2, pp. 1247–1258, 2014.

[37] J. Shi, C. Wang, and P. An, "Loop-Based Coding Reactive Tabu Search for Comprehensive Optimization in Distribution Networks," in *2011 Asia-Pacific Power and Energy Engineering Conference*, 2011, pp. 1–4.

[38] J. Shi, C. Wang, P. An, and H. Zhu, "Comparision of coding schemes for distribution networks reconfiguration," in *2011 4th International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT)*, 2011, no. 2009, pp. 1816–1819.

[39] S. S. F. Souza, R. Romero, and J. F. Franco, "Artificial immune networks Copt-aiNet and Opt-aiNet applied to the reconfiguration problem of radial electrical distribution systems," *Electr. Power Syst. Res.*, vol. 119, pp. 304–312, Feb. 2015.

[40] M. F. Sulaima, M. N. M. Nasir, N. H. Shamsudin, M. Sulaiman, and W. M. Dahalan, "Implementation of Modified EPSO Technique in 69kV Distribution Network Reconfiguration for Losses Reduction," *Int. J. Eng. Technol.*, vol. 7, no. 2, pp. 502–509, 2015.

[41] S. Sultana and P. K. Roy, "Oppositional krill herd algorithm for optimal location of capacitor with reconfiguration in radial distribution system," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 78–90, Jan. 2016.

[42] A. Swarnkar, N. Gupta, and K. R. Niazi, "Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization," *Swarm Evol. Comput.*, vol. 1, no. 3, pp. 129–137, Sep. 2011.

[43] B. Tomoiagă, M. Chindriş, A. Sumper, R. Villafafila-Robles, and A. Sudria-Andreu, "Distribution system reconfiguration using genetic algorithm based on connected graphs," *Electr. Power Syst. Res.*, vol. 104, pp. 216–225, Nov. 2013.

[44] C. Wang, A. Zhao, H. Dong, and Z. Li, "An Improved Immune Genetic Algorithm for Distribution Network Reconfiguration," in *2009 International Conference on Information Management, Innovation Management and Industrial Engineering*, 2009, pp. 218–223.
[45] Xiaoli Meng, Limei Zhang, Pengwei Cong, Wei Tang, Xiaohui Zhang, and Dechang Yang, "Dynamic reconfiguration of distribution network considering scheduling of DG active power outputs," in *2014 International Conference on Power System Technology*, 2014, no. Powercon, pp. 1433–1439.
[46] H. R. Esmaeilian and R. Fadaeinedjad, "Energy Loss Minimization in Distribution Systems Utilizing an Enhanced Reconfiguration Method Integrating Distributed Generation," *IEEE Syst. J.*, vol. 9, no. 4, pp. 1430–1439, Dec. 2015.
[47] W.-C. Wu and M.-S. Tsai, "Application of simple examination and retrieval procedure in evolutionary algorithms for feeder reconfiguration," *Eur. Trans. Electr. Power*, vol. 21, no. 1, pp. 1054–1071, Jan. 2011.
[48] T. Niknam, M. Zare, J. Aghaei, and E. A. Farsani, "A new hybrid evolutionary optimization algorithm for distribution feeder reconfiguration," *Appl. Artif. Intell.*, vol. 26, no. 1–2, pp. 182–182, Jan. 2012.
[49] T. Niknam, E. Azadfarsani, and M. Jabbari, "A new hybrid evolutionary algorithm based on new fuzzy adaptive PSO and NM algorithms for Distribution Feeder Reconfiguration," *Energy Convers. Manag.*, vol. 54, no. 1, pp. 7–16, Feb. 2012.
[50] A. A. A. Esmin and G. Lambert-Torres, "Application of particle swarm optimization to optimal power systems," *Int. J. Innov. Comput. Inf. Control*, vol. 8, no. 3A, pp. 1705–1716, 2012.
[51] E. Azad-Farsani, M. Zare, R. Azizipanah-Abarghooee, and H. Askarian-Abyaneh, "A new hybrid CPSO-TLBO optimization algorithm for distribution network reconfiguration," *J. Intell. FUZZY Syst.*, vol. 26, no. 5, pp. 2175–2184, 2014.
[52] K. D. Mistry and R. Roy, "Impact of demand response program in wind integrated distribution network," *Electr. Power Syst. Res.*, vol. 108, pp. 269–281, Mar. 2014.
[53] S. Chen, Z. Chen, X. Zhang, C. Su, and W. Hu, "Optimal reactive power and voltage control in distribution networks with distributed generators by fuzzy adaptive hybrid particle swarm optimisation method," *IET Gener. Transm. Distrib.*, vol. 9, no. 11, pp. 1096–1103, Aug. 2015.
[54] H. Liang, "An Improved Optimization Algorithm for Network Skeleton," *Teh. Vjesn. Gaz.*, vol. 22, no. 6, pp. 1359–1363, 2015.
[55] W.-T. Huang, T.-H. Chen, H.-T. Chen, J.-S. Yang, K.-L. Lian, Y.-R. Chang, Y.-D. Lee, and Y.-H. Ho, "A Two-stage Optimal Network Reconfiguration Approach for Minimizing Energy Loss of Distribution Networks Using Particle Swarm Optimization Algorithm," *Energies*, vol. 8, no. 12, pp. 13894–13910, 2015.
[56] R. Jabbari-Sabet, S.-M. Moghaddas-Tafreshi, and S.-S. Mirhoseini, "Microgrid operation and management using probabilistic reconfiguration and unit commitment," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 328–336, Feb. 2016.
[57] B. R. Jouybari, M. Hosseini, and Z. Byagowi, "Optimal Placement of Distributed Generators and Reconfiguration of Distribution Systems for Loss Reduction Using Genetic Algorithm," *Int. Rev. Electr. Eng.*, vol. 6, no. 2, B, pp. 1007–1012, 2011.
[58] A. E. Milani and M. R. Haghifam, "An evolutionary approach for optimal time interval determination in distribution network reconfiguration under variable load," *Math. Comput. Model.*, vol. 57, no. 1–2, pp. 68–77, Jan. 2013.
[59] A. Zidan and E. F. El-Saadany, "Distribution system reconfiguration for energy loss reduction considering the variability of load and local renewable generation," *Energy*, vol. 59, pp. 698–707, Sep. 2013.
[60] C. Wang and Y. Gao, "Determination of Power Distribution Network Configuration Using Non-Revisiting Genetic Algorithm," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3638–3648, Nov. 2013.
[61] N. Gupta, A. Swarnkar, and K. R. Niazi, "Distribution network reconfiguration for power quality and reliability improvement using Genetic Algorithms," *Int. J. Electr. Power Energy Syst.*, vol. 54, pp. 664–671, Jan. 2014.
[62] W. M. Dahalan, H. Mokhlis, R. Ahmad, A. H. Abu Bakar, and I. Musirin, "Simultaneous Network Reconfiguration and DG Sizing Using Evolutionary Programming and Genetic Algorithm to Minimize Power Losses," *Arab. J. Sci. Eng.*, vol. 39, no. 8, pp. 6327–6338, Aug. 2014.
[63] X. Lei, H. Wu, Y. Shi, and P. Shi, "Distribution network reconfiguration based on parallel genetic membrane computing," *J. Intell. Fuzzy Syst.*, vol. 29, no. 5, pp. 2287–2298, Aug. 2015.
[64] T. Niknam, E. A. Farsani, M. Nayeripour, and B. B. Firouzi, "Hybrid Fuzzy Adaptive Particle Swarm Optimization and Differential Evolution Algorithm for Distribution Feeder Reconfiguration," *Electr. Power Components Syst.*, vol. 39, no. 2, pp. 158–175, Jan. 2011.
[65] A. R. Malekpour, T. Niknam, A. Pahwa, and A. Kavousi Fard, "Multi-Objective Stochastic Distribution Feeder Reconfiguration in Systems With Wind Power Generators and Fuel Cells Using the Point Estimate Method," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1483–1492, May 2013.
[66] M. J. Kasaei, "Distribution Network Reconfiguration for Optimal Operation of Distributed Generation with Ant Colony Algorithm," *Prz. ELEKTROTECHNICZNY*, vol. 88, no. 12A, pp. 255–258, 2012.
[67] A. Y. Abdelaziz, R. A. Osama, and S. M. Elkhodary, "Distribution Systems Reconfiguration Using Ant Colony Optimization and Harmony Search Algorithms," *Electr. Power Components Syst.*, vol. 41, no. 5, pp. 537–554, Mar. 2013.
[68] S. Abazari and M. H. Soudejani, "A new technique for efficient reconfiguration of distribution networks," *Sci. Iran.*, vol. 22, no. 6, pp. 2516–2526, 2015.
[69] C. H. N. D. R. Barbosa, R. F. Alexandre, and J. A. De Vasconcelos, "A practical codification and its analysis for the generalized reconfiguration problem," *Electr. Power Syst. Res.*, vol. 97, pp. 19–33, Apr. 2013.
[70] L. W. de Oliveira, E. J. de Oliveira, F. V. Gomes, I. C. Silva, A. L. M. Marcato, and P. V. C. Resende, "Artificial Immune Systems applied to the reconfiguration of electrical power distribution networks for energy loss minimization," *Int. J. Electr. Power Energy Syst.*, vol. 56, pp. 64–74, Mar. 2014.
[71] M. N. Muhtazaruddin, J. J. Jamian, G. Fujita, M. a. Baharudin, M. W. Wazir, and H. Mokhlis, "Distribution Network Loss Minimization via Simultaneous Distributed Generation Coordination with Network Reconfiguration," *Arab. J. Sci. Eng.*, vol. 39, no. 6, pp. 4923–4933, Jun. 2014.
[72] F. R. Alonso, D. Q. Oliveira, and A. C. Zambroni de Souza, "Artificial Immune Systems Optimization Approach for Multiobjective Distribution System Reconfiguration," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 840–847, Mar. 2015.
[73] A. Botea, J. Rintanen, and D. Banerjee, "Optimal Reconfiguration for Supply Restoration With Informed A* Search," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 583–593, Jun. 2012.
[74] L. W. de Oliveira, F. D. S. Seta, and E. J. de Oliveira, "Optimal reconfiguration of distribution systems with representation of uncertainties through interval analysis," *Int. J. Electr. Power Energy Syst.*, vol. 83, pp. 382–391, Dec. 2016.
[75] S. S. F. Souza, R. Romero, J. Pereira, and J. T. Saraiva, "Artificial immune algorithm applied to distribution system reconfiguration with variable demand," *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 561–568, Nov. 2016.
[76] S. . Nawaz, M. . Imran, A. K. . Sharma, and A. . Jain, "Optimal feeder reconfiguration and DG placement in distribution network," *Int. J. Appl. Eng. Res.*, vol. 11, no. 7, pp. 4878–4885, 2016.
[77] Y. Lu, J. Wu, and L. Hao, "Multi-objective distribution network reconfiguration with distributed generations based on improved MOBPSO algorithm," *Dianli Xitong Baohu yu Kongzhi/Power Syst. Prot. Control*, vol. 44, no. 7, pp. 62–68, 2016.
[78] M. R. Haghifam, A. Moradkhani, and S. M. Miri Larimi, "Risk-based reconfiguration of active electric distribution networks," *IET Gener. Transm. Distrib.*, vol. 10, no. 4, pp. 1006–1015, Mar. 2016.
[79] S. Chen, W. Hu, and Z. Chen, "Comprehensive Cost Minimization in Distribution Networks Using Segmented-Time Feeder Reconfiguration and Reactive Power Control of Distributed Generators," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 983–993, Mar. 2016.
[80] T. Zhang, S. Shi, and X. Xu, "Distribution network reconfiguration with distributed generation based on improved quantum binary particle swarm optimization," *Dianli Xitong Baohu yu Kongzhi/Power Syst. Prot. Control*, vol. 44, no. 4, pp. 22–28, 2016.
[81] H. . Yi, B. . Zhang, H. . Wang, Y. . Wu, G. . Yuan, and R. . Lü, "Distribution network dynamic reconfiguration method for improving distribution network's ability of accepting DG,"

Dianwang Jishu/Power Syst. Technol., vol. 40, no. 5, pp. 1431–1436, 2016.

[82] A. A. Zidan, M. F. Shaaban, and E. F. El-Saadany, “Impacts of Feeder Reconfiguration on Renewable Resources Allocation in Balanced and Unbalanced Distribution Systems,” *Electr. Power Components Syst.*, vol. 44, no. 9, pp. 974–989, May 2016.

[83] A. Asrari, S. Lotfifard, and M. Ansari, “Reconfiguration of Smart Distribution Systems With Time Varying Loads Using Parallel Computing,” *IEEE Trans. Smart Grid*, pp. 1–11, 2016.

[84] C. Yan, Q. Luo, and Y. Chen, “An Efficient Hybrid Evolutionary Optimization Algorithm combining Ant Colony Optimization with Simulated Annealing,” *Int. J. Digit. Content Technol. its Appl.*, vol. 5, no. 8, pp. 234–240, Aug. 2011.

[85] W. Hui, Z. Liang, W. Wei, Z. Fei-fan, J. Xiu, and Z. Hong, “Distribution network reconstruction based on improved ant colony algorithm of directional pheromones,” in *The 27th Chinese Control and Decision Conference (2015 CCDC)*, 2015, pp. 1243–1247.

[86] Y. Xiang, J. Liu, M. Li, and W. Wang, “Two-stage Control Strategy for Structure Optimization of Faulted Distribution System with Distributed Generation,” *Electr. Power Components Syst.*, vol. 42, no. 6, pp. 595–604, Apr. 2014.

[87] M. R. Nayak, “Optimal feeder reconfiguration of distribution system with distributed generation units using HC-ACO,” *Int. J. Electr. Eng. Informatics*, vol. 6, no. 1, pp. 107–128, 2014.

[88] N. I. Voropai and B . Bat-Undraal, “Multicriteria Reconfiguration of Distribution Network with Distributed Generation,” *J. Electr. Comput. Eng.*, vol. 2012, pp. 1–8, 2012.

[89] M. J. . Kasaei and H. . Norouzi, “Reconfiguration of distribution network with dispersed generations based on ant colony algorithm,” *Int. Rev. Model. Simulations*, vol. 4, no. 6, pp. 3113–3118, 2011.

[90] H. . Takano, J. . Murata, Y. . Maki, and M. . Yasuda, “Improving the search ability of tabu search in the distribution network reconfiguration problem,” *J. Adv. Comput. Intell. Intell. Informatics*, vol. 17, no. 5, pp. 681–689, 2013.

[91] A. Y. Abdelaziz, R. A. Osama, and S. M. El-Khodary, “Reconfiguration of distribution systems for loss reduction using the hyper-cube ant colony optimisation algorithm,” *IET Gener. Transm. Distrib.*, vol. 6, no. 2, p. 176, 2012.

[92] H. a. Abdelsalam, A. Y. Abdelaziz, and V. Mukherjee, “Optimal PMU placement in a distribution network considering network reconfiguration,” in *2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014]*, 2014, pp. 191–196.

[93] A. Ahuja, A. Pahwa, B. K. Panigrahi, and S. Das, “Pheromone-Based Crossover Operator Applied to Distribution System Reconfiguration,” *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4144–4151, Nov. 2013.

[94] W. An, Q. Zhou, X. Zhang, Y. Qin, and W. Chen, “An immune genetic algorithm based approach for distribution system reconfiguration,” in *2010 Sixth International Conference on Natural Computation*, 2010, pp. 92–95.

[95] J. Chen, F. Zhang, and Y. Zhang, “Distribution Network Reconfiguration Based on Simulated Annealing Immune Algorithm,” *Energy Procedia*, vol. 12, pp. 271–277, 2011.

[96] F. Wang, Y. Li, Q. Liu, and X. Ji, “A multi-agent Immune-based Co-Taboo search algorithm for distribution network reconfiguration,” in *2011 International Conference on Electrical and Control Engineering*, 2011, no. 3, pp. 953–956.

[97] W. Wu and M. Tsai, “Application of Enhanced Integer Coded Particle Swarm Optimization for Distribution System Feeder Reconfiguration,” *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1591–1599, Aug. 2011.

[98] A. M. Othman, A. A. El-Fergany, and A. Y. Abdelaziz, “Optimal Reconfiguration Comprising Voltage Stability Aspect Using Enhanced Binary Particle Swarm Optimization Algorithm,” *Electr. Power Components Syst.*, vol. 43, no. 14, pp. 1656–1666, Aug. 2015.

[99] G. Graditi, M. L. Di Silvestre, D. La Cascia, E. Riva Sanseverino, and G. Zizzo, “On multi-objective optimal reconfiguration of MV networks in presence of different grounding,” *J. Ambient Intell. Humaniz. Comput.*, vol. 7, no. 1, pp. 97–105, Feb. 2016.

[100] V. Farahani, B. Vahidi, and H. A. Abyaneh, “Reconfiguration and Capacitor Placement Simultaneously for Energy Loss Reduction Based on an Improved Reconfiguration Method,” *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 587–595, May 2012.

[101] S. Garcia-Martinez and E. Espinosa-Juarez, “Reconfiguration of power systems by applying Tabu search to minimize voltage sag indexes,” in *2011 North American Power Symposium*, 2011, pp. 1–6.

[102] S. García-Martínez and E. Espinosa-Juárez, “Optimal Reconfiguration of Electrical Networks by Applying Tabu Search to Decrease Voltage Sag Indices,” *Electr. Power Components Syst.*, vol. 41, no. 10, pp. 943–959, Jul. 2013.

[103] P. Mitra and G. K. Venayagamoorthy, “Implementation of an Intelligent Reconfiguration Algorithm for an Electric Ship’s Power System,” *IEEE Trans. Ind. Appl.*, vol. 47, no. 5, pp. 2292–2300, Sep. 2011.

[104] C. Wang, Y. Liu, and Y. Zhao, “Application of dynamic neighborhood small population particle swarm optimization for reconfiguration of shipboard power system,” *Eng. Appl. Artif. Intell.*, vol. 26, no. 4, pp. 1255–1262, Apr. 2013.

[105] F. Shariatzadeh, C. B. Vellaithurai, S. S. Biswas, R. Zamora, and A. K. Srivastava, “Real-Time Implementation of Intelligent Reconfiguration Algorithm for Microgrid,” *IEEE Trans. Sustain. Energy*, vol. 5, no. 2, pp. 598–607, Apr. 2014.

[106] H. Arasteh, M. S. Sepasian, and V. Vahidinasab, “An aggregated model for coordinated planning and reconfiguration of electric distribution networks,” *Energy*, vol. 94, pp. 786–798, 2016.

[107] H. . b Wu, X. . Lei, B. . Liu, Y. . Lu, and G. . Xu, “Membrane computing based genetic algorithm for dynamic reconfiguration of distribution network with dividing time and considering electric vehicles and wind turbines,” *Diangong Jishu Xuebao/Transactions China Electrotech. Soc.*, vol. 31, no. 2, pp. 196–205 and 220, 2016.

[108] Z. Ghofrani-Jahromi, M. Kazemi, and M. Ehsan, “Distribution Switches Upgrade for Loss Reduction and Reliability Improvement,” *IEEE Trans. Power Deliv.*, vol. 30, no. 2, pp. 684–692, Apr. 2015.

[109] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in *Proceedings of ICNN’95 - International Conference on Neural Networks*, 1995, vol. 4, pp. 1942–1948.

[110] J. Kennedy and R. C. Eberhart, “A discrete binary version of the particle swarm algorithm,” in *1997 IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation*, 1997, vol. 5, pp. 4104–4108.

[111] S. Su, C. Lu, R. Chang, and G. Gutierrez-Alcaraz, “Distributed Generation Interconnection Planning: A Wind Power Case Study,” *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 181–189, Mar. 2011.

[112] S. Jazebi, M. Moghimi Haji, and R. A. Naghizadeh, “Distribution Network Reconfiguration in the Presence of Harmonic Loads: Optimization Techniques and Analysis,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1929–1937, Jul. 2014.

[113] B. Amanulla, S. Chakrabarti, and S. N. Singh, “Reconfiguration of Power Distribution Systems Considering Reliability and Power Loss,” *IEEE Trans. Power Deliv.*, vol. 27, no. 2, pp. 918–926, Apr. 2012.

[114] J. H. Holland, “Adaptation in Natural and Artificial Systems,” University of Michigan Press, Ann Arbor, 1975.

[115] A. Zidan, M. F. Shaaban, and E. F. El-Saadany, “Long-term multi-objective distribution network planning by DG allocation and feeders’ reconfiguration,” *Electr. Power Syst. Res.*, vol. 105, pp. 95–104, Dec. 2013.

[116] G. L. Storti, M. Paschero, A. Rizzi, and F. M. Frattale Mascioli, “Comparison between time-constrained and time-unconstrained optimization for power losses minimization in Smart Grids using genetic algorithms,” *Neurocomputing*, vol. 170, pp. 353–367, Dec. 2015.

[117] S. H. Alemohammad, E. Mashhour, and M. Saniei, “A market-based method for reconfiguration of distribution network,” *Electr. Power Syst. Res.*, vol. 125, pp. 15–22, Aug. 2015.

[118] V. C. do Nascimento, G. Lambert-Torres, C. I. de A. Costa, and L. E. Borges da Silva, “Control model for distributed generation and network automation for microgrids operation,” *Electr. Power Syst. Res.*, vol. 127, pp. 151–159, Oct. 2015.

[119] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by Simulated Annealing,” *Science (80-.).*, vol. 220, no. 4598, pp. 671–680, 1983.

[120] F. Nournejad, R. Kazemzade, and A. S. Yazdankhah, “A multiobjective evolutionary algorithm for distribution system reconfiguration,” in *16th Conference on Electrical Power Distribution Networks (EPDC)*, 2011, pp. 1–7.

[121] R. Belkacemi and A. Feliachi, “Multi-agent design for power distribution system reconfiguration based on the artificial immune system algorithm,” in *Proceedings of 2010 IEEE International Symposium on Circuits and Systems*, 2010, pp. 3461–3464.

[122] F. Glover, “Tabu Search—Part I,” *ORSA J. Comput.*, vol. 1, no. 3, pp. 190–206, Feb. 1989.

[123] F. Glover, “Tabu Search—Part II,” *ORSA J. Comput.*, vol. 2, no. 1, pp. 4–32, 1990.

[124] E. Espinosa Juarez and A. Hernandez, “An Analytical Approach for Stochastic Assessment of Balanced and Unbalanced Voltage Sags in Large Systems,” *IEEE Trans. Power Deliv.*, vol. 21, no. 3, pp. 1493–1500, Jul. 2006.

[125] V. S. Santos, P. R. V. Felipe, J. R. G. Sarduy, N. a. Lemozy, A. Jurado, and E. C. Quispe, “Procedure for Determining Induction Motor Efficiency Working Under Distorted Grid Voltages,” *IEEE Trans. Energy Convers.*, vol. 30, no. 1, pp. 331–339, Mar. 2015.

[126] J. Candelo and H. Hernández, “Distributed Generation Placement in Radial Distribution Networks using a Bat-inspired Algorithm,” *DYNA*, vol. 82, no. 192, pp. 60–67, Aug. 2015.